How Strong is Your Tinder Game?

Strategic Two-Sided Search in Swipe-Based Dating Apps

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Overview

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2. Theoretical Model
3. Results
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Introduction – Context, Research Objectives, and Contributions

- Tinder: a two-sided decentralised matching platform with 70+ million users
  - Agents are presented with suggestions to swipe left or right on; matches occur given a double coincidence of wants
- Love is a tricky game; Tinder makes it trickier
  - Stage interaction: simple static game of incomplete information
  - Dynamic interactions are harder due to platform features and repeated game complexities
- **When should a user 'swipe right'?**
  - What arrangements emerge as equilibria?
  - How do exogenous factors affect the above?

- Related Work
  - Two-Sided Search: Burdett and Wright (1998), Adachi (2003), Mekonnen (2019)
  - Mean Field Games: Jovanovic and Rosenthal (1988), Iyer et al. (2014)
  - Modern Dating App Interactions: Kanoria and Saban (2021), Olmeda (2021), Tyson et al. (2016)
- Contributions
  - One of the first *strategic* models for swipe-based dating platforms.
  - An addition to the emerging literature on mean-field game theory.
  - Case study for computational techniques applied to game theory.

Theoretical Model – Setup

- Time is discrete and indexed $t = 0, 1, 2, ...$
- Agents are periodically suggested partners from the opposite sex, with attractiveness $\theta_t \in \Theta := [0, 1]$
- Actions $a_t \in \mathcal{A} := \{0, 1\}$ are chosen while facing a *swiping budget* $b_t \in \mathcal{B} := \{0, ..., B\}$ that follows LOM: $b_{t+1} = b_t - a_t$
- Matching payoff is $u(\theta_t)$, where $u(\cdot)$ is strictly increasing, bounded, and satisfies $u(0) = 0$.
- We restrict attention to stationary Markov strategies: $\mu, \omega : \Theta \times \mathcal{B} \to \Delta\mathcal{A}$
- Each period, λ_m men and λ_w women enter the platform.
- Incoming agents' attractiveness is sampled i.i.d from distributions $F_m(\theta)$ and $F_w(\theta)$.
- Agents leave the platform:
  - *Endogenously*, when they exhaust their budgets
  - *Exogenously*, at a death rate of $(1 - \delta)$
- Let N_m^t, N_w^t denote the masses of men and women in the platform at period t.
- Let $M^t(\theta, b), W^t(\theta, b)$ be the joint distributions over men and women at t.

Theoretical Model – Characterising the Steady State

- The Tinder Market is defined by $\Psi^t = (N_m^t, N_w^t, M^t, W^t)$
  - Note that this is endogenously dependent on μ, ω
- We seek steady state such that $\Psi^t = \Psi^{t+1} = \ldots = \Psi(\mu, \omega)$
- Theorem 1 solves for this, and shows that θ and b are independent.
- Furthermore, it is shown that $M_\theta(\theta; \mu, \omega) = F_m(\theta)$.

Theorem (The Tinder Steady State)

Fix stationary Markov strategies μ, ω and let:

$$\rho_b^m = \int_\Theta \mu(\theta', b)\, dW_\theta(\theta'; \mu, \omega),$$

$$z_b^m = \prod_{i=1}^{B-b} \frac{\delta \rho_{B-i+1}^m}{\left(1 - \delta(1 - \rho_{B-i}^m)\right)}, \quad z_B^m = \left(1 - \delta(1 - \rho_B^m)\right)$$

Then there exists a unique market steady state (with an analogous case for women) characterised by:

$$N_m(\mu, \omega) = \lambda_m \left(\frac{z_B^m - \delta z_1^m \rho_1^m}{(1 - \delta) z_B^m} \right),$$

$$M(\theta, b; \mu, \omega) = F_m(\theta) \left(\frac{(1 - \delta)}{z_B^m - \delta z_1^m \rho_1^m} \right) \sum_{i=1}^{b} z_i^m$$

Theoretical Model – The Love Search Problem

- We consider a man's search problem in a given steady state Ψ against a given ω
- With friction-less search, men get suggestions at a rate $\tau = \min\{\frac{N_w}{N_m}, 1\}$
  - Define $\alpha = \frac{\tau\delta}{1-\delta(1-\tau)}$ as the effective discounting rate

$$V_m(\theta, b) = \max_{\{a_t\}_{t=0}^{\infty}} \mathbb{E}_\Psi \left[\sum_{t=0}^{\infty} \alpha^t U_m(\theta_t, a_t) \mid \theta_0, b_0 = \theta, b \right]$$

$$\text{s.t. } \theta_t \sim F_w, \quad b_{t+1} = b_t - a_t$$

$$b_t \in \mathcal{B}, \quad a_t \in \mathcal{A}$$

- Agents maximise the sum of discounted expected *ex-interim* payoffs $U_m(\theta, a_t)$
  - The optimal strategy $\widetilde{\mu}(\theta, b; \omega, \Psi)$ is a cutoff $\widetilde{\mu}_b$ at the point of indifference

$$\begin{aligned} V_m(\theta, b) \; = \; \max \Big\{ \; & U_m(\theta) + \alpha \, \mathbb{E}_\Psi \Big[V_m(\theta', b-1) \Big], \\ & \alpha \, \mathbb{E}_\Psi \Big[V_m(\theta', b) \Big] \; \Big\} \end{aligned}$$

$$u(\widetilde{\mu}_b) \; = \; \alpha u(\widetilde{\mu}_b) F_w(\widetilde{\mu}_b) + \alpha u(\widetilde{\mu}_{b-1}) \Big(1 - F_w(\widetilde{\mu}_{b-1}) \Big) + \int_{\widetilde{\mu}_b}^{\widetilde{\mu}_{b-1}} \alpha u(\theta') \, dF_w(\theta') \tag{1}$$

$$u(\widetilde{\mu}_1) \; = \; \alpha u(\widetilde{\mu}_1) F_w(\widetilde{\mu}_1) + \int_{\widetilde{\mu}_1}^{1} \alpha u(\theta') \, dF_w(\theta') \tag{2}$$

Theoretical Model – Stationary Markov Equilibrium

Definition (Stationary Markov Equilibrium)

A pair of strategies μ^*, ω^* parametrised by cutoffs μ_b^*, ω_b^*, $\forall b \in \mathcal{B}$, and a steady-state market Ψ^* is a Stationary Markov Equilibrium (SME) if:

1. $\mu_b^* = \widetilde{\mu}(b; \Psi^*, \omega^*), \quad \forall b \in \mathcal{B}$
2. $\omega_b^* = \widetilde{\omega}(b; \Psi^*, \mu^*), \quad \forall b \in \mathcal{B}$
3. $\Psi^* = \Psi(\mu^*, \omega^*)$

- (1) and (2) imply that μ^* and ω^* are *ex-ante* best-responses to each other given Ψ^*.
- (3) implies that Ψ^* is self-consistent: key property of oblivious/mean-field equilibria.
- We solve for this equilibrium computationally by formulating it as a system $\mathbf{E}(\mu, \omega)$ of non-linear equations.
- This is then re-framed it as a least-squares optimisation problem that can be solved numerically.

Results – The Optimal Swiping Rule and Value Function

Results – Comparative Statics on The Swiping Rule

Results – Comparative Statics on The Market

Reflections and Further Research

- Cool stuff, but why does it matter?
  - 6.6 million paid Tinder subscribers by the end of 2020.
  - Main subscription features: no swiping caps or location limits.
  - What is the value of subscriptions? Are people wasting their money?
- Next Steps: Dynamics
  - How can the s.s arise as a limiting state?
  - Best-Response Dynamics? Fictitious Play?
  - Bayesian learning?
- Next Steps: Noisy Search
  - How does 'profile noise' change the search problem for agents?
  - Use of simulations for stability checks
- Next Steps: Platform Design
  - How can Tinder set welfare-maximizing swiping caps?
  - Can directed search mechanisms lead to convergence onto stable matches?
  - Challenge: limited observability

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